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The Impacts of Metering and Climate Conditions on Residential Electricity Demand

The Case of Albania

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Abstract

Albania is among the most vulnerable countries to external energy shocks and climatic conditions, because of its high dependency on hydropower for electricity. Given highly volatile international energy prices and expected global warming, it is becoming increasingly important to manage the demand for electricity. However, the country has long been faced with a significant problem of electricity metering. About one-third of total energy is lost for technical and nontechnical reasons. This paper estimates the residential demand function by applying a two-stage system equation method for an endogenous censored variable, because the lack of metering makes the electricity consumption partially observable for the econometrician. It is found that metering is important to curb non-essential electricity use by households. The electricity demand could also be reduced by raising the first block rate and lowering the second block rate and the threshold between the two blocks. In addition, weather conditions and home appliance ownership would affect the demand for electricity. But the latter looks more influential than the former.

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THE IMPACTS OF METERING AND CLIMATE CONDITIONS ON RESIDENTIAL ELECTRICITY DEMAND: THE CASE OF ALBANIA

January 2011

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JEL classifications: C34; C36; H54; L11; L94.

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I. Introduction

In recent years it has become increasingly important to understand the demand for electricity, because of highly volatile international energy prices and global warming expected in the future. How to manage the consumer demand for electricity remains a challenge for many developing and transition economies. To this end, metering is essential, because it is generally difficult to design an effective tariff structure without sufficient meters installed. Lack of metering also complicates other governance issues, such as electricity theft, and generates a significant adverse effect on the sector's financial viability and the country's energy security and growth.

This paper examines the residential electricity demand in Albania, using micro data from the country's household surveys. Particularly, it casts light on the potential impacts of metering and climatic conditions. To estimate the unbiased demand function, several important econometric issues need to be addressed, such as simultaneity between price and quantity, self-selection of metering, and partially observable electricity consumption. By using a two-stage method, the paper will show that metering is an important determinant of the residential demand for electricity. It will also show that higher-than-usual temperature and increasing ownership of air conditioners would likely push up the electricity demand in Albania.

Metering is a fundamental step for successful utilities to promote energy efficiency and financial sustainability. This may be intuitively obvious, but it is not as simple as it looks. For instance, the U.K. experience indicates that metering per se may not always be required for the utility service provision. In the United Kingdom, historically, only about one-third of domestic water users are metered. Hence, if the capacity of supply is sufficient and the demand is well predicted even in the absence of meters, utilities may not have to install meters. But this is very difficult in practice.[1]

[1] In the United Kingdom, water services have not been charged based on metering until recently. Given the 2005 drought and severe water shortage, water supply companies embarked upon the metering program. By legislation, water companies in areas of serious water stress will be able to compulsorily meter customers from

In general, without proper metering, reading and billing, there is no incentive for consumers to rationalize their use of energy. Overconsumption is a typical problem caused by the lack of utility meters. When a customer has no meter, a certain amount of normative consumption is often assumed. The norm is designed to be consistent with how much people are actually using. But this is merely a proxy. Of particular note, the norm is usually fixed. Therefore, low levels of metering will provide wrong price incentives to customers. In addition, low metering may create a broader distortion in the whole price structure. This will affect not only unmetered but also metered customers. As a result, utility operators tend to be faced with a significant risk of financial nonviability. For instance, in Africa it is estimated that only 50 percent of electricity generated is paid for, because of low collection rates as well as high technical losses (Antmann, 2009).

In Albania, technical and nontechnical electricity transmission and distribution losses have been substantial for a long time. The system losses amounted to 49 percent in 2000 and have been declining gradually. The donor community has been supporting the government's efforts toward appropriate meter installation in Albania.[2] But the losses were still 35 percent in 2009, which is markedly high by any standards. Besides technical losses, one of the alleged reasons for the high losses is that metering might not be functioning properly. In Albania there has been concern about destruction, disconnection and manipulation of installed meters. Consequently, the country is estimated to lose about 2 percent of GDP of unaccounted-for energy every year. Not surprisingly, the state-owned electricity company was faced with significant financial difficulties until recently.[3]

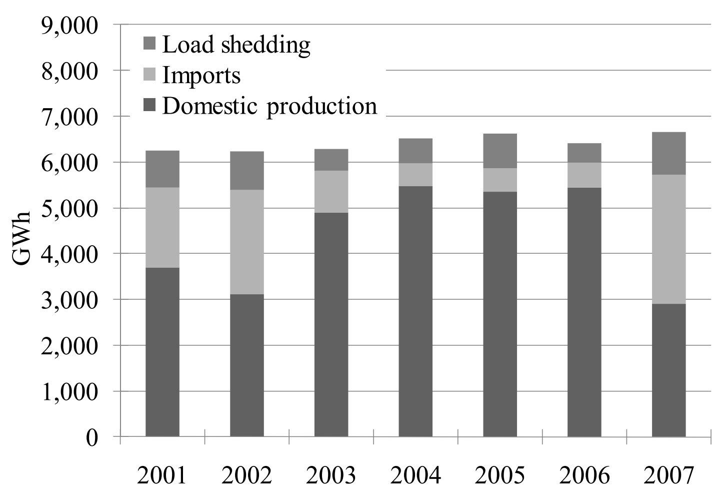
2010. The government expects the installation rates to reach at least 80 percent for most water supply companies by 2020 (Ofwat web).

[2] The World Bank reallocated some resources of the Power Transmission and Distribution Project (IDA Credit No. 2826-ALB) to financing for residential consumer meters in 2001-2003 (PAD 14532-ALB; 27049-ALB). However, the metering situation does not seem to have changed much during the assistance period.

[3] To deal with these systemic problems, the government decided to introduce the private sector into the electricity distribution segment in 2009. Note that the paper does *not* intend to provide any policy implication to the currently ongoing electricity privatization process in Albania. The main objective of this paper is more technical to estimate the effects of metering and climate change on the energy demand.

Climate change may add to the complexity of the problems in the energy sector. In Albania, energy efficiency is becoming more important from both energy security and climate change perspectives. The country is dependent more than 95 percent on hydropower for domestic electricity generation and therefore considered among the most vulnerable countries to external energy shocks and climatic conditions. In the past, severe droughts posed significant challenges on Albania (ESMAP, 2009). Meanwhile, the demand for electricity is steadily increasing with economic growth. As the result, if drought happens as in 2002 and 2007, the country will have to import a large amount of energy from abroad at significantly high costs. Otherwise, massive electricity supply cuts will be unavoidable (Figure 1). Therefore, long-term energy planning and demand management continue to be critical for Albania to achieve energy security and economic growth. To this end, metering is expected to have an important role to play in incentivizing consumers to reduce non-essential use of electricity. The efficient energy use will mitigate the need for investment in new electricity generation capacity and thus contribute to emissions reduction.

Figure 1. Electricity Transmission and distribution losses (percent of total)



Source: KESH data.

Pricing is a key policy instrument to manage the demand for energy in general. It is not only about the level of prices but also about the structure of tariff. If prices are low and the demand is price-elastic, raising the prices can be a useful policy measure to contain the electricity demand. In practice, however, the price structure is often complex and reflects various policy considerations, such as affordability of the poor and promotion of energy-intensive industries. Therefore, the impacts of raised tariff may not be straightforward. An increasing block tariff mechanism is, for instance, a common practice to encourage large-volume customers to use electricity wisely, while keeping the prices for the poor relatively low. However, this discriminatory pricing may adversely affect the households' incentives to install a proper meter or falsify metering readings; people do not want to be applied to higher rates. Hence, the net impacts may remain debatable.

The current paper analyzes household data from the Albania's Living Standards Measurement Studies (LSMS) for 2002–2005. Because there are multiple endogeneity issues, it applies the Nelson-Olsen (1978) two-stage estimator, which models a system of censored and non-censored equations. The remainder of the paper is organized as follows: Section II summarizes the theoretical and practical issues related to metering. Section III discusses the possible effects of climatic conditions on the electricity demand, in particular in the context of Albania. Section IV develops an empirical model and discusses various econometric issues to estimate the electricity demand. Section V describes our data, and Section VI presents the main estimation results. Section VII discusses robustness of the estimation results and some policy implications. Section VIII then concludes.

II. Metering in Theory and Practice

Metering is an essential policy instrument to motivate customers to use electricity wisely. In theory, a simple model can show that people would overconsume electricity in the absence of metering. There is no incentive for overconsuming customers to install a meter, even if the cost of meter installation is small. By contrast, unmetered customers who are consuming less than the norm will have strong incentives to install a meter, if the installation cost is small enough. This self-selective process would end up with the overconsumption situation where unmetered customers would overconsume the utility services. One might think that overconsumption would not occur if the normative amount of consumption, which is applied for unmetered customers, were consistent with what they are actually consuming. However, a fundamental difficulty exists for operators to set the optimal norm and other tariff structure under the low metering circumstances. See the Appendix for further detail.

Proposition: There is no incentive for overconsuming customers to install a meter.

Overconsumption has several important implications to utility operations. First, it means that the norm is too low. Therefore, a certain amount of consumption is left unbilled. Many countries in Sub-Saharan Africa are suffering from this problem (Antmann, 2009). Second, the too low norm in turn makes the average price upward biased. This is because someone has to pay unbilled electricity that unmetered customers are consuming without paying. In this regard, non-metering is a problem for not only unmetered but also metered customers; the upward biased tariff is applied to all the customers. Finally, if an overconsuming customer newly installs a meter, the overall average tariff can be reduced, holding everything else constant. Thus, for unmetered consumers, there is a tradeoff between the benefits from and costs of meter installation. In theory, however, even if this price reduction effect is taken into account, the above proposition still holds: unmetered customers would have no incentive to move from an unmetered to metered regime (see the Appendix).

Besides overconsumption, low levels of metering would also make it difficult for policy makers or operators to implement advanced tariff mechanisms, such as tariff-based subsidies. Theoretically, conditional cash transfers are preferable to support energy consumption of the poor. However, tariff-based subsidies, such as increasing block tariffs, are still prevalent across countries (Komives *et al.*, 2006). In the increasing block tariff structure, a relatively low marginal price is set for low-volume customers and a higher rate for large-volume consumers. This aims to not only address affordability for the poor—presumably, low-volume customers—but also motivate large-volume consumers to refrain from non-essential use of electricity.[4] In Albania, the increasing block tariff is mainly intended for the latter. Overconsumption by large-volume consumers is the primary target of the demand management.

A practical challenge in implementing the discriminatory pricing is how to select an optimal threshold between the blocks. The lifeline consumption can be one possible option. In Georgia, it is estimated that the lifeline consumption would be 125 kWh per month, which will cover lighting and a modest number of home appliances, but not heating or air conditioning (Lampieti *et al.*, 2007). But the optimal level differs across countries or cities (e.g., Komives *et al*., 2005). The Cape Verde's block tariff mechanism had a much lower first block threshold, which was set at 40 kWh in 2001/02. By contrast, in Sao Tome and Principe the threshold was much high at 300 kWh in 2000/01 (Komives *et al.*, 2006). Essentially, without knowing how much energy individual consumers are actually consuming, it is difficult to design an optimal stepped tariff structure.

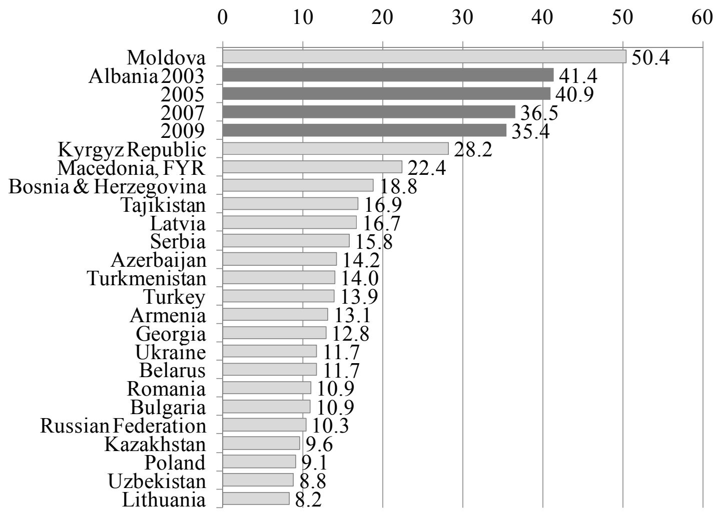
Regardless of its importance, there is no systematic data available on metering across countries. Fragmented evidence may exist. It indicates that metering remains a challenge in many developing and transition countries. Important, experience shows that the metering problem can be addressed quickly if appropriate policies are in place. In Tbilisi, the electricity meter installation rate was 38 percent in 2000 but improved to 76 percent in 2002 (Lampietti *et al*., 2007). In Andhra Pradesh, India, only 42 percent of inflowing energy was metered and billed in 1998/99 (Antmann, 2009). In Bangladesh consumer payments accounted for only 55 percent of energy generated (Lovei and McKechnie, 2000).

One of the proxies that represent the existing meter penetration and how effectively meters are functioning is the rate of electricity transmission and distribution losses. The variable is available for most countries (Figure 2). Nontechnical losses are partly attributable to the lack

[4] There is argument as to whether the implicit assumption that low-income households are low-volume consumers is reasonable. It may depend on the size of family and dwelling and other factors (e.g., Besant-Jones, 2006).

of metering. High system losses, whether technical or nontechnical, would incur large implicit fiscal deficits along with underpricing and nonpayment. This is often a significant problem in the electricity sector of developing countries. The quasi-fiscal deficits can amount to as much as 1 to 2 percent of GDP.[5]

Figure 2. Electricity Transmission and distribution losses (percent of total)



Sources: KESH data for Albania; World Development Indicators for other countries.

In Albania, the electricity system losses have been a long controversial issue, because they are extremely high by both global and regional standards (Figure 2). The losses, though gradually declining, were estimated at 35 percent in 2009. Despite some recent improvements, the Albania's system is still losing about one-third of total energy produced (and imported).

On paper, the meter penetration rate is already high in Albania. But the remaining deficiency has long been persistent, negatively affecting the whole governance in the electricity sector. According to the ERE data, about 100,000 electricity customers or about 11 percent of total

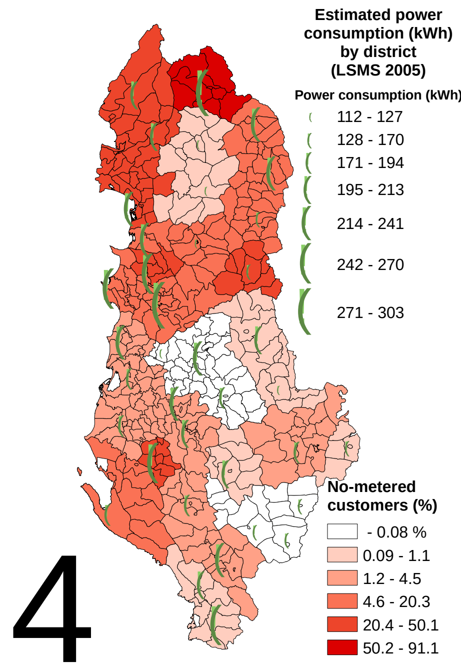
[5] In Africa, the quasi-fiscal deficits in the electricity sector were estimated at almost zero to 4.7 percent of GDP with an average of 0.84 percent (Briceno-Garmendia *et al.*, 2008). In the Europe and Central Asia (ECA) region, the deficits were estimated at nearly zero to 1.3 percent of GDP in 2003 (World Bank, 2006).

customers still did not have functioning electricity meters on March, 2008.[6] This national figure may not appear so critical. But in some northern districts, the vast majority of households remain to be equipped with electricity meters. The progress of meter installation is significantly different across regions (Figure 3). In addition, improper metering practices, such as malfunctioning meters, falsification of meter readings and illegal connections, have been real concern.

Who do not yet have electricity meters? As discussed, the northern districts are lagging behind in this regard. By rural-urban classification, rural residents are less likely to have meters (Table 1). Based on household characteristics, it is also found that unmetered households are relatively poor; their average monthly income is significantly lower than metered households in a statistical sense. In addition, unmetered households have fewer home appliances. It seems that there is certain correlation among household income, meter installation, home appliance holding, and remoteness of their residences. Where metering is less prevalent, residents seem to have used relatively more electricity per month (see Figure 3).

[6] There are some discrepancies in the data on the share of unmetered customers. While the ERE data come from the electricity operator and are considered comprehensive, the LSMS data are partial and can be reported wrongly by sample households. The metering share may have been improving in recent years. According to the latest 2008 LSMS data, the share of unmetered households is about 3 percent.

Figure 3. Meter installation rate and electricity consumption in Albania



Source: Author's drawing based on LSMS 2005 and ERE data.

Table 1. Household characteristics by electricity meter installation

Variable	With meter			Without meter			Wilcoxon rank-sum test statistics (z)
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	
Monthly income	4184	39094	55092	578	31758	32911	–5.64 ***
Number of household members	4184	4.516	1.593	578	4.810	1.637	4.60 ***
Urban resident	4184	0.679	0.467	578	0.484	0.500	–9.20 ***
Number of home appliances:							
Color TV	4184	1.154	0.512	578	1.028	0.466	–6.00 ***
Video	4184	0.373	0.504	578	0.280	0.461	–4.21 ***
Refrigerator	4184	0.969	0.269	578	0.919	0.341	–4.26 ***
Freezer	4184	0.012	0.121	578	0.019	0.149	1.38
Washer	4184	0.739	0.449	578	0.576	0.505	–8.06 ***
Dishwasher	4184	0.019	0.136	578	0.019	0.149	–0.26
Electric or gas stove	4184	0.809	0.435	578	0.734	0.501	–4.15 ***
Air conditioner	4184	0.087	0.340	578	0.050	0.287	–3.29 ***
Water Boiler	4184	0.645	0.505	578	0.545	0.512	–4.43 ***
Computer	4184	0.088	0.291	578	0.040	0.204	–3.94 ***

Note: *** indicates the 1% significance level.

In developing countries, low levels of metering tend to complicate other governance problems in the electricity sector. First, without reliable metering systems, electricity operators have little incentive to improve the system efficiency, because of their low accountability. The reason is that technical and nontechnical losses are not distinguishable without sufficient meters. Therefore, the system losses may or may not be considered as their faults. The lack of capital investment in the network, for instance, may not fall on utilities. In Andhra Pradesh, the utility's efforts to reduce the system losses began with recognition of the existing technical losses and theft. The technical losses, of which the former official estimate was 18 percent, were projected to be 38 percent (Antmann, 2009). This is a politically challenging yet essential step to strengthen the utility's accountability.

Second, the absence of metering may also weaken enforceability of payments, even if the norm is applied to unmetered customers. The reason is that people can always claim to have used nothing. In addition, given the weak metering practices, utility officials would likely have incentives to practice irregular billing and over-charging. On the other hand, customers may have incentives to pay a bribe and ask for falsification of meter readings. A survey in South Asian countries indicates that about 20 to 30 percent of customers are faced with endemic petty corruption through meter readers (Transparency International; World Bank, 2009a). The same problem has been observed in the water sector. More than 70 percent water utility staff responded that meter falsification is very common to lower bills. And 41 percent of interviewed customers actually made informal payment to falsify meter readings (Davis, 2004; World Bank, 2008).

To deal with these problems, the private sector participation in the distribution network is one of the options that governments can take. Experience shows that it can promote proper metering, reading, billing and collection quickly, thereby improving the sector's governance and performance. Apparently, nontechnical system losses are an obvious revenue leakage from the systems.[7] Therefore, private operators are willing to make efforts toward proper metering.[8] In Colombia, when an electricity distribution company serving the capital Bogota

[7] The other area is obviously technical losses in the system. The relative easiness to address the problems depends on country. In Albania, about half of the total system losses are estimated to be attributed to nontechnical losses.

[8] Practically, a phased approach may be useful to address the metering issue. Because a small number of large consumers often represent a large amount of energy sales and revenue in the electricity sector. Hence, the

was unbundled and privatized, the company, CODENSA, installed 164,000 new meters and replaced 156,000 damaged or tampered meters. Along with other reforms, the company successfully decreased the total distribution losses from 22 percent in 1997 to 9 percent in 2007 (Antmann, 2009). The marked improvement in payment collections in Tbilisi was also brought about by the distribution company privatization (Lampietti *et al*., 2007).

From the analytical point of view, it is worth recalling that the current paper focuses on the pre-privatization period to examine the effects of metering and other exogenous conditions, not investigating the privatization effect. In Albania, the distribution system was privatized in 2009, and the distribution company intends to achieve fully working universal metering by 2010. It is too early to assess the performance, but the similar improvements are expected to the above-mentioned countries. Privatization can be one of the driving forces behind potential improvements in metering and other operational performance. Notably, however, the privatization effect is out of the scope of this paper.

It is also important to note that the estimation results of this paper should be interpreted as a marginal effect of metering on the energy demand. In Albania, the metering rate has already been high at least on paper, as shown above. Thus, the direct impact of increased metering on the demand or utility revenue may not be significant.[9] However, as discussed, increasing metering is expected to help rationalize the pricing as well. Therefore, the pricing effect to be estimated is also important. The general implications from the estimation results could be referred to for discussing the metering problem in other countries where meters are missing to a greater extent.

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regularization of metering, billing and collection should be started from these large-volume customers. Then, smaller customers could gradually be covered.

[9] In fact, the share of flat rate billing is not significant in Albania. It was about 9 percent in 2009.

III. Climate and Electricity Demand

The electricity demand depends on climatic conditions, such as maximum temperature during the summer and precipitation during the rainy season. This is an important implication to the current analysis. The literature shows that the climate would affect the electricity demand. With seasonal data in India, for instance, the price elasticity is found to range from –0.51 in the monsoon months to –0.29 in the summer months (Filippini and Pachauri, 2004). Although the elasticities generally look moderate, the demand in summer is more inelastic than that in the monsoon season. This implies that people would need more electricity in summer. In the United States, the electricity demand is also found to be dependent on daily temperature and humidity, in particular in summer (Hausman *et al*., 1979). Davis (2008) indicates that the household electricity demand is shifted by daily rainfall.

The electricity demand is also affected by the ownership of home appliances. The residential electricity demand can be explained by whether households own air conditioners, water heaters, dishwashers, clothes washers and freezers (Hausman *et al*., 1979). Especially, air conditioners may have a large impact on the demand for electricity. Reiss and White (2005) show that the price elasticity for households with central or air conditioning is three times higher (in absolute terms) than that for those who have no air conditioning. As the result, the impact of air conditioning can be substantial, as in the United States during the late 1980s. It is estimated to have reached about one-third of the total electricity peak demand (Andrew, 1989). In Hong Kong, heating, ventilation and air-conditioning are found to be the single largest electricity end-user, accounting for 30 to 60 percent of the total electrical demand during the hot summer months of July and August (Lam *et al.*, 2003). The same phenomenon may happen in many developing countries, because the air conditioner ownership increases in close relation to income growth (e.g., Matsukawa and Ito, 1998; Fernandez, 2000; Matsukawa, 2001).

Seasonality may have important implications for the demand for electricity. In Albania, the electricity use for heating and water heating is currently creating significant seasonal peak demand during the winter (Figure 4). In summer, the demand is relatively low, because residential ownership of air conditioners remains small. But this has been increasing in recent years (Table 2). As the result, the demand for peak electricity during the summer may pick up, possibly adding more pressures on the need for additional and diverse peak load capacity. Especially, it is projected that summer runoff would considerably decline over the long run (ESMAP, 2009). Other home appliances, such as electric stoves and water boilers, are also considered to generate the electricity demand to a greater or lesser extent (Table 3).[10]

Figure 4. Monthly electricity supply in Albania

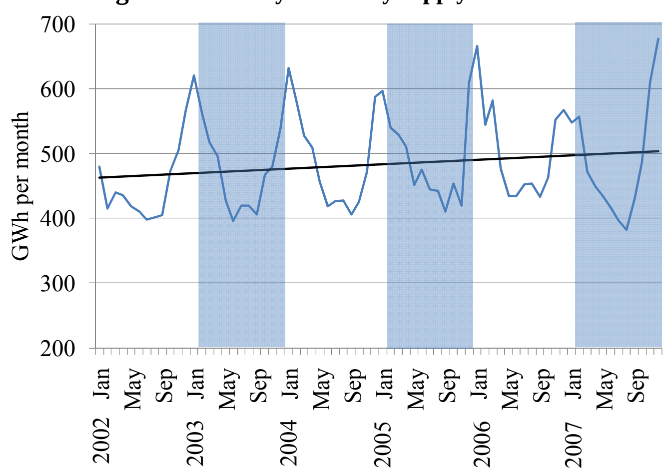


Table 2. Electricity consumption, climate conditions and home appliance ownership in Albania

	2002	2003	2004	2005
Number of observations	642	1,180	1,332	1,608
Electricity consumption:				
Monthly electricity consumption (kWh)	371.2	361.2	351.0	349.0
Monthly payment for electricity (lek)	2,060.7	2,171.6	2,379.2	2,282.9
Weather conditions:				
Monthly average high temperature (°C)	25.7	29.3	24.3	25.3
Monthly precipitation (mm)	73.3	29.7	85.9	59.6
Average number of home appliances:				
Air conditioner	0.04	0.09	0.40	0.29
TV	1.07	1.10	1.17	0.50
Washer	0.69	0.67	0.47	0.42
Electric stove	0.75	0.76	0.47	0.40
Water boiler	0.55	0.60	0.50	0.50

Sources: Albania LSMS data and weather data from IEWE, Albania.

[10] Though, the following analysis may not be able to capture the potential impacts of some home appliances, such as electric stoves, because the data relies on the household surveys implemented during the spring and summer months.

Table 3. Sample coverage by month

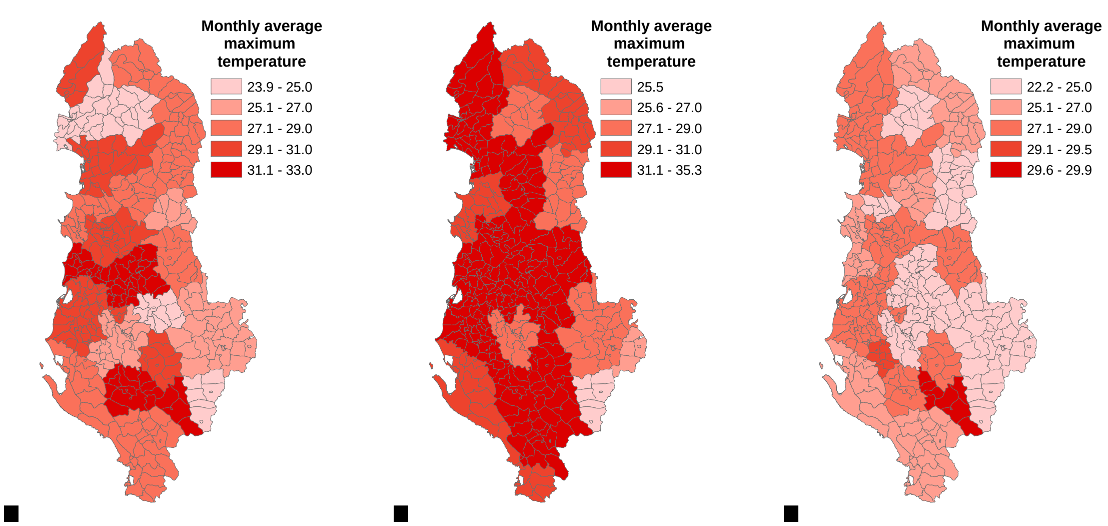
	Year							
	2002		2003		2004		2005	
Month	Obs.	%	Obs.	%	Obs.	%	Obs.	%
4	29	4.5						
5	324	50.5	569	48.2	648	48.7	1,058	65.8
6	244	38.0	594	50.3	668	50.2	538	33.5
7	45	7.0	17	1.4	16	1.2	12	0.8
Total	642	100.0	1,180	100.0	1,332	100.0	1,608	100.0

Source: Albania LSMS data.

In Albania the climate differs from year to year and depends on location. This variation is, of course, of particular importance to identify the climatic impacts on the electricity demand in our empirical model. In the sample period, the month of June in 2003 was hotter than usual. In that year, air conditioners and other seasonal home appliances may have contributed to increasing the residential electricity demand. In addition, climate conditions vary significantly across region in the country. The northern and eastern mountainous regions are relatively cool in Albania. By contrast, the coastal and southern areas are hotter (Figure 5). In 2003, temperature was high, exceeding 30°C almost all over the country. Summer 2004 was relatively cool. Correspondingly, more precipitation fell over most of the country in 2004 (Figure 6). Summer 2002 was driest among the sample years.

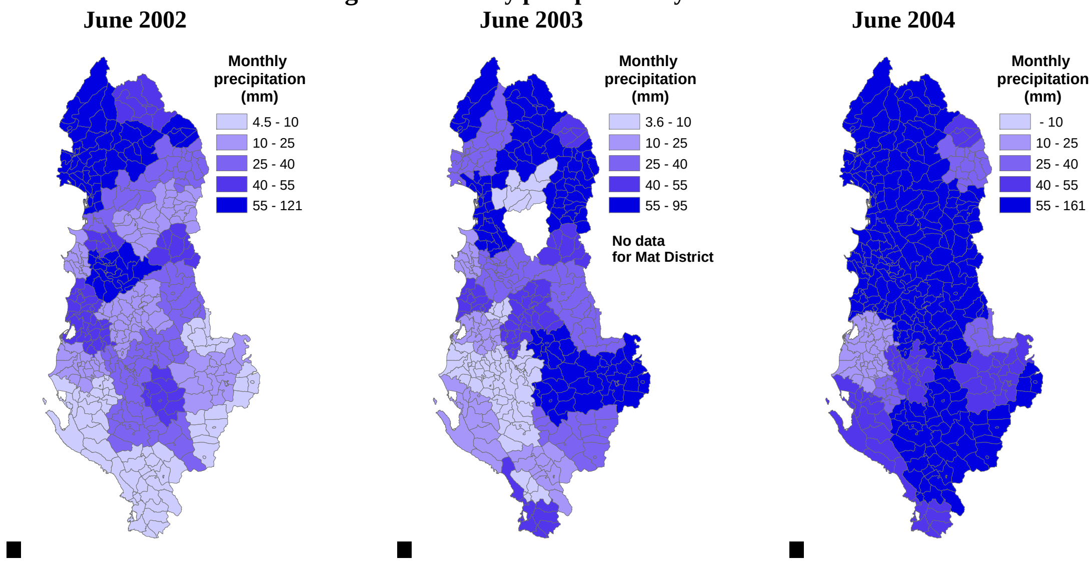
Figure 5. Monthly average maximum temperature by district

June 2002 June 2003 June 2004



Source: Author’s drawing based on weather data from IEWE, Albania.

Figure 6. **Monthly precipitation by district**

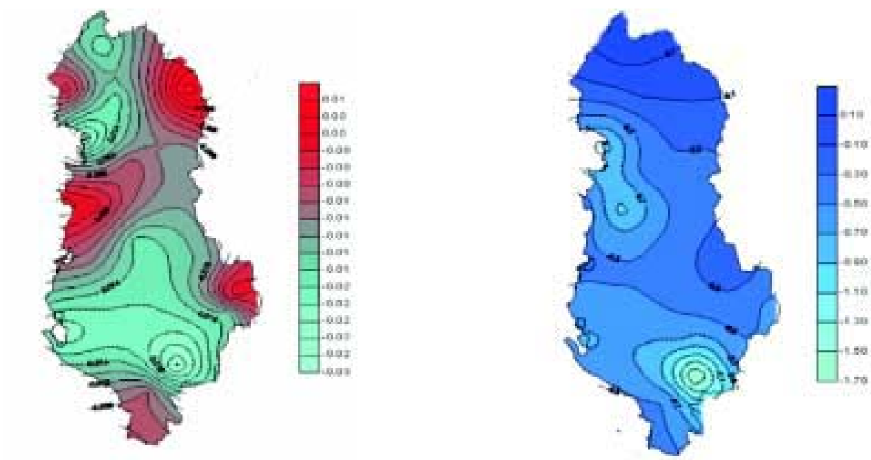


Source: Author's drawing based on weather data from IEWE, Albania.

From the longer time perspective, the climate will be changing. The following analysis of this paper will remain static to the extent that the data are collected during the fairly short period of time and no dynamic consumer response, such as home appliance purchasing, is assumed. However, it is still indicative to see the impacts of climatic conditions by evaluating the estimated demand function with respect to expected climate change. In Albania, average temperature increased around 1 °C in the past 30 years, while precipitation declined especially during winter and spring (Figure 7). In the future, temperature is projected to increase 1.2–1.8 °C by 2050 and 2.1–3.6 °C by 2100, and more droughts and less precipitation are expected (ESMAP, 2009). Therefore, on one hand the electricity demand may continue increasing unless significant improvements in energy efficiency of the economy take place. On the other hand, the country's water resources may become scarcer, intensifying the country's climate vulnerability. If more droughts happen, as in 2002 and 2007, the country will be faced with significant supply shortage, which would lead to either massive power outages or costly power imports from abroad. Hence, energy efficiency and electricity demand management will remain a critical policy issue for Albania.

Figure 7. Climate changes from 1960 to 1990 in Albania

Annual temperature (1960-90) **Annual precipitation (1960-90)**



Source: Ministry of Environment, Albania (2002).

IV. EMPIRICAL MODEL

To investigate the electricity demand, the following demand function is estimated:

$$q_i^* = \alpha_1 I_i + X_{1i}'\beta_1 + u_{1i} \tag{1}$$

where q_i^* is the true amount of service consumed by household *i*, and I_i is an indicator function for meter installation. X_1 includes a final marginal price applied for each consumer, denoted by *MP* and other covariates. For weather conditions, two variables are included in X_1: monthly average maximum temperature (*TEMP*) and monthly precipitation (*PREC*). In principle, the simple OLS could estimate Equation (1) consistently, if metering and other explanatory variables, including *MP*, were exogenous and data were perfectly observed. In reality, there are a number of econometric issues—both traditional and untraditional— to estimate the equation. Without dealing with these problems, the metering effect α_1 and other coefficients β_1 would be biased. On the traditional side, there are at least five econometric issues in the demand estimation literature.

Endogeneity of price and quantity. First, the OLS estimator is biased because of the traditional simultaneity problem between price and quantity. In a general supply-demand model, price and quantity are jointly determined. Thus, without extraneous information (i.e., instrumental variables), the model cannot be identified. One might think that this simultaneity problem would not matter much in the electricity sector, because prices might be regulated and considered to be determined exogenously. However, the block tariff structure creates another possibility of endogeneity. Under the block tariff framework, consumers can choose the marginal price that would be applied by deciding how much electricity they consume. In addition, the block pricing can also cause a measurement error. This is because consumers are normally uncertain about which marginal rate would be eventually applied before they receive the bills (Deller *et al*., 1986).[11] Therefore, the potential endogeneity of price and quantity needs to be addressed in the presence of block pricing.

In Albania, the marginal rate varies depending on customer classification and how much electricity is used (Table 4). During the sample period: 2002-2005, the country adopted a two block tariff structure where the first block rate was kept about half of the second block rate. While the lower block tariff was increased from 4 lek to 4.5 lek per kWh in 2004, the second block rate was gradually raised from 8 lek to 9 lek throughout the sample period. At the same time, the threshold between the two marginal tariffs was also decreased substantially. This means that the potential benefits from the lower rate were cut on a quantity basis, while the marginal price was also raised. These price changes are expected to have reduced the people's use of electricity, if the demand is price-elastic.

[11] Time-of-day electricity pricing is one possibility to incentivize consumers to monitor their actual consumption periodically, as experimented in Hausman *et al.* (1979). However, it is still open to argument whether consumers can really adjust their consumption based on the real-time meter readings.

Table 4. Electricity tariff structure in Albania

Year	1st block rate (lek/kWh)	2nd block rate (lek/kWh)	Threshold (kWh)	Normative consumption (kWh) 1/	
				Urban	Rural
2002	4.0	8.0	300.0	356.9	244.4
2003	4.0	8.1	300.0	356.9	244.4
2004	4.5	8.9	220.0	363.8	237.0
2005	4.5	9.0	210.0	363.8	237.0

1/ Average across districts for the summer period.
Source: Electricity Regulatory Entity, Albania.

How much people would respond to changes in marginal prices, *MP*, depends on the price elasticity of demand. In the literature the estimates vary significantly, depending on country, period and data being analyzed, and methodology adopted. According to a classical literature review (Taylor, 1975), the price elasticity is estimated at –1.02 to –2.00 for residential users and –1.25 to –1.94 for industrial consumers. A more recent meta analysis shows that the average price elasticity of residential electricity demand is –0.35 in the short run and –0.85 over the long run (Espey and Espey, 2004). With regional aggregate data, Bernstein and Griffin (2005) find that the residential electricity elasticities in the United States are –0.24 and –0.32 in the short and long run, respectively. With micro data, Wilder and Willenborg (1975) estimate the elasticity at –1.31 in South Carolina in 1973. Reiss and White (2005) report an elasticity of –0.39 for California households during the period: 1993-1997. With more detailed micro data on an hourly basis, the time-of-day price elasticity is estimated to ranges from –0.13 during peak hours and –0.22 during non-peak hours in Connecticut (Hausman *et al.*, 1978).

Nordin's difference. Second, net positive (negative) consumer welfare caused by the increasing (decreasing) block tariff should be included in X_1, but it will be another endogenous variable for the same reason as above mentioned. Note that the price variable in the demand function must be a marginal tariff rate of the final block that each consumer faces, rather than the average price (computed as the total bill divided by total consumption). This is basically because neoclassical economic theory assumes that people consume goods or services given a marginal price.[12] Accordingly, those who consume more electricity than the first block threshold will benefit from the implicit income effect caused by differences among the marginal rates. This is called the Nordin's difference variable—denoted by *D*—and is calculated by subtracting the actual total bill from what would be paid if the final block rate were applied for the total consumption (Nordin, 1976).[13] In the following analysis, the endogeneity associated with the Nordin's difference will be addressed along with the above marginal price endogeneity issue.

Dependency on household appliances. Third, as discussed, the residential demand for electricity is likely to depend on home appliance holdings (Dubin and McFadden, 1984; Reiss and White, 2005). This can be considered as a long-term effect, because home appliances are generally durable goods and it takes some time for consumers to decide to purchase a new home appliance in response to other exogenous factors, such as income growth and climate change. Normally, the increasing ownership of home appliances will result in increases in the electricity demand. But this may not always be the case. For instance, if a household replaces an old appliance with an energy efficient one, the demand may decline. A counterargument is that improved energy efficiency may induce consumers to use more home appliances, as in the case of automobiles (e.g., Small and van Dender, 2007; Frondel *et al*., 2008). Large-volume consumers may have stronger incentives to purchase energy efficient appliances. Therefore, the decision of purchasing home appliances is potentially self-selective and may have to be treated as an endogenous variable (Davis, 2008).

In the following analysis, nonetheless, the household appliances ownership is assumed exogenous, because the sample period of our data is relatively short, covering only four years: 2002–2005. During this period, home appliance ownership was not changed

[12] There is a view that households are rarely aware of the detailed price structure or marginal prices. But the marginal and average prices are eventually related to one another (e.g., Wilder and Willenborg, 1975; Terza and Welch, 1982; Nauges and van den Berg, 2009).

[13] This is also referred to as virtual income by Hausman *et al.* (1979).

significantly, as shown in Table 1. Though, the appliance ownership is still an important determinant of the residential demand for electricity. Thus, a number of dummy variables for various household appliances are included in X_1 as independent variables.

Alternative energy choice. Fourth, if there are any important alternative energy sources, such as liquefied petroleum gas (LPG) and firewood, those substitutes should be incorporated in the estimation model. Ideally, with sufficient data the model should be estimated as a system of multiple demand functions (e.g., Nauges and van den Berg, 2009). However, data are not always available. Even in a single equation model, the demand function can also involve prices of alternative sources (Filippini and Pachauri, 2004). An alternative approach may be to introduce another equation for deciding whether or not to connect the service (Basani *et al*., 2008). Behind this approach, it is implicitly assumed that some alternatives exist. Given this specification, the conventional Hausman self-selection model can be used for estimation.

In the case of Albania, there are few important alternative energy choices for households. The country has already achieved almost universal access to electricity network, though the quality of supply still remains problematic. The access rate was 99.97 percent in 2005. People may use LPG for heating and especially for cooking, but the use of gas may be relatively limited, in particular in urban areas.[14] By contrast, many firms are equipped with their own private backup facilities.[15] Therefore, no alternative choice is explicitly considered in our empirical model. The paper takes into account whether households are using electricity or LPG for major household activities, such as heating and cooking. This is expected to

[14] There is some difference between the LSMS data and people's perception about the energy alternative. While the LSMS data indicate that some amount of household expenditure was spent for LPG and firewood, people perceive that they are largely dependent on electricity for energy. This is partly because there is a considerable difference in living conditions between urban and rural areas. In rural areas, firewood is often an alternative energy source. According to the 2005 LSMS, some 70 percent of rural households used some firewood for heating or lighting, while only 30 percent of urban residents used.

[15] According to the 2005 LSMS, only about 3 percent of households answered that an alternative energy source for lighting was power generator. On the other hand, about 80 percent of firms in the country have their own backup generators, which are estimated to have generated some 30 percent of firm electricity consumption in 2006 (Iimi, 2010).

capture some demand shifts caused by the ways of using different energy sources. As will be seen, our estimation results indicate that the use of electricity or LPG has certain but not much explanatory power to the electricity demand.

Sample bias. Household surveys often have a sample bias problem. Respondents can always choose not to provide answers (Yoo, 2007). It is often pointed out that the amount of electricity consumption reported in household surveys might be deviated from the amount that households actually consumed. In Georgia, for instance, it is found that household surveys overstated the actual payments received by a power company (Lampietti *et al*., 2007). In our sample, there is no crucial evidence that Albania's household surveys suffer from the sample bias problem.

Instruments. The current paper adopts three instrumental techniques to deal with the endogeneity associated with the marginal price and Nordin's difference variable. First, the marginal price and Nordin's difference variables are instrumented by their predicted values according to the simple expansion of the definition of the Nordin's difference variable. To obtain the predicted values, the actual bill payment is regressed on a constant term and the quantity of consumption:

$$\begin{aligned} D_j &= Bill_{ij} - MP_j q_{ij} \\ Bill_{ij} &= \gamma_{1j} + \gamma_{2j} q_{ij} + \varepsilon_{ij} \end{aligned}$$

where $Bill_{ij}$ is the amount of bill payment for customer i, who is faced with jth block marginal rate. ε_{ij} represents an error term. The marginal price and Nordin's difference variable can be instrumented by $\hat{\gamma}_2$ and $\hat{\gamma}_1$, respectively (Hewlett, 1977). However, there may remain concern about the fact that the total bill is still a function of quantity and marginal price. Therefore, total bills may still feedback onto quantity (Deller *et al.*, 1986).

The second technique is the Terza's (1986) two-stage probit approach, which essentially transforms the endogeneity question to the consumer self-selection problem. It is shown that the marginal rate applied is dependent on the consumer welfare, which is supposed to be maximized by consumer's self-selection of quantity. In the two-block tariff case, the consumer's self-selection depends on two variables: the sum of two marginal tariffs and the sum of two net income transfers. These can be used as exogenous variables for the selection equation (Welch and Terza, 1982).

Third, the marginal price and Nordin's difference variable can be instrumented by the exact rate structure characteristics. This is a more common approach in the literature (e.g., Wilder and Willenborg, 1975; Deller *et al.*, 1986; Nieswiadomy and Molina, 1989). The basic idea is that the rate schedule is used to linearize a budget set that each household faces (Hausman and Wise, 1976; Hausman *et al.*, 1979).

The paper does *not* use the other alternative approach, which uses household location as an instrument (e.g., Naugas and van den Berg, 2009). While this approach has the advantage of taking any unobserved measurement errors into account, it does not allow us to examine any effects of location-specific covariates, which are often of particular interest from the economic policy point of view. In addition, in the case of Albania it does not appear to be appropriate to assume that a household's location choice is independent of electricity availability or consumption. The average consumption of electricity appears to differ systematically among districts in Albania, as shown in Figure 2.

Econometric issues related to metering. Up to here all the econometric issues are traditional; without any further complication, the above instrumental variable approaches could estimate Equation (1) consistently. However, an additional problem arises if the observed amount consumption, denoted q_i^* in the equation, is incorrect due to lack of metering, or if the meter installation (I_i) in the equation can be treated as endogenous. In the case of Albania, both seem to be applicable, as discussed in the previous sections.

At the beginning, suppose that the predetermined normative amount would be unbiased. That is, unmetered customers would consume more or less the predetermined normative amounts.

Also, suppose that metering would not be self-selected—for instance, metering is completely mandatory. Of course, it is assumed that a vector of X_1 controls for everything else related to the residential electricity demand. Then, no explanatory power should be left in the metering variable, *I*, in Equation (1). Once the traditional endogeneity issues are addressed properly, the two-stage or instrumental variable regression could have an insignificant coefficient α_1 and estimate other parameters consistently. Conversely, if it turns out that metering reduces consumption, it means that unmetered customers would be overconsuming electricity for non-essential purposes, as theory predicts. In other words, the norm would be underestimated.

Hypothesis: The normative amount is set consistently; thus, metering does not matter to electricity consumption.

If the hypothesis be rejected, the estimation model needs to be modified with the fact that the norm would likely be underestimated taken into consideration. The reason is that the dependent variable is now considered to be only partially observable due to the absence of metering. If a customer has no meter, all we can know is that she would likely consume at least the normative amount, $\bar{q}$.[16] Unlike metered customers, it cannot be observed exactly how much electricity unmetered customers are actually consuming. Hence, the actual amount of consumption, q^*, is partially observable, or more precisely, censored at the normative value if consumer *i* does not have a meter.

$$q_i = \begin{cases} q_i^* & \text{if } I_i = 1 \\ \bar{q}_i & \text{otherwise} \end{cases} \qquad (2)$$

where *q* is the observed amount of consumption in the data. Note that in Albania the norm varies depending on household location and season. Therefore, $\bar{q}$ is not necessarily unique for everyone in the nation.

[16] Technically, both over- and underconsumption cases can be examined econometrically; but the paper will focus on the former case, which is more plausible in reality and fits our data. It means that *q* is censored at the norm when a household is not equipped with a meter.

In addition, the decision of whether to install a meter is potentially endogenous, because it is determined by the amount of consumption, which may or may not be observable by the econometrician. But each household knows its true amount of consumption, q_i^*. Depending on this, each family decides whether or not to install a meter. This selection seems to be possible in the context of Albania; recall that falsification of meter readings and illegal connections have long been significant concerns. Therefore, it is potentially reasonable to assume that *I* is endogenously determined according to the following selection mechanism:

$$I_i = \begin{cases} 1 & \text{if } I_i^* = \alpha_2 q_i^* + X_{i2}'\beta_2 + u_{i2} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where I^* is a latent variable for meter installation and *I* is a dichotomous observable realization. The selection mechanism is assumed to follow the tariff structure that each household is faced with. Especially, if the norm is low, the incentive not to install a meter would be strong, because the bill payment for unmetered customers will be small no matter how much electricity they consume. If the norm is set relatively low, people would be more likely to stay unmetered as the block rates increase. This is because people could expect more "savings" by fixing the amount of consumption, compared to the payment that would be charged if metered. Therefore, X_2 include the tariff structure information, such as block rates, threshold and norm, as well as X_1.

Consequently, we have the following two-equation system with censored and observed endogenous variables:

$$\begin{aligned} q_i &= \begin{cases} q_i^* & \text{if } I_i = 0 \qquad \text{where } q_i^* = \alpha_1 I_i + X_{1i}'\beta_1 + u_{1i} \\ \bar{q}_i & \text{otherwise} \end{cases} \\ I_i &= \alpha_2 q_i^* + X_{2i}'\beta_2 + u_{i2} \end{aligned} \tag{4}$$

For computational simplicity, I is treated as a continuous variable, instead of binary. Note that I is observable in our case. This can be estimated by the Nelson-Olsen (1978) two-stage estimation technique. First, the reduced form for q is estimated by the tobit method over $X = [X_1, X_2]$, and the reduced form for I is estimated by OLS over X. Then, the equation of q is estimated by the tobit method replacing I with $\hat{I}$. Letting the covariance matrix of this estimator be V_0, the asymptotic covariance for $(\hat{\alpha}_1, \hat{\beta}_1)$ can be written by:

$$V(\hat{\alpha}_1, \hat{\beta}_1) = (G'V_0^{-1}G)^{-1} + d(G'V_0^{-1}G)^{-1}G'V_0^{-1}(X'X)^{-1}V_0^{-1}G(G'V_0^{-1}G)^{-1} \quad (5)$$

where $G = [\Pi_2, J_1]$. Π_2 is a vector of the coefficients from the first stage OLS regression for I. J_1 is the matrix consisting of zeros and ones so that $XJ_1 = X_1$. d is calculated by $d = \alpha_1^2\sigma_2^2 - 2\alpha_1\sigma_{12}$. While σ_1^2 is a variance of the error term of the first stage tobit estimation, σ_{12} is a covariance between the two reduced form equations. See Amemiya (1979) and Maddala (1983) for further detail.

V. Data

The paper uses household surveys in Albania for four consecutive years: 2002-2005. It pools the four surveys. Note that the number of observations for 2002 is relatively small, because of lack of information required for the analysis (see Table 3). The total number of observations is 4,762. The summary statistics is presented in Table 5. The sample average of monthly power consumption is about 350 kWh with a wide range from less than 1 kWh to over 4,000 kWh per month. The metering rate is about 88 percent. The average marginal rate faced by residential customers is about 8 lek per kWh. Note that all the monetary variables are normalized to the 2005 constant term. In theory, the Nordin's difference variable should be positive under the increasing block tariff regime. However, it can be negative in the real data, because of possible false data reports on bill payments and censored data on electricity consumption. In case the Nordin's difference is negative, it is assumed to take a small but positive number to avoid logarithms of zero.[17]

Two weather-related variables are selected: monthly average of maximum temperature and monthly precipitation. These data are available and presumably considered to be most relevant to the electricity demand in Albania. Besides two weather-related variables, monthly household income and the number of household members are included in X_1 and X_2. To control the extent to which individual households rely on electricity and gas for their basic home appliances, a number of dummy variables representing electricity use and the number of home appliances held by each household are also included.[18] A dummy variable for urban areas is introduced to control for a systematic heterogeneity between urban and rural areas. Urban residents seem to use more electricity; their income is higher, and they own more electric appliances.

The model includes a variable that represents frequency of power outages, which is measured by the average duration of power outages per day. Households experienced about 3 hours and half of power outages during the sample period. For obvious reasons, electricity cannot be consumed if power outages occur. This captures some undervaluation of the demand in the observed data.

As instrumental variables, two block rates, a threshold between the two blocks and the normative amount of consumption applied to those who have no meter. Recall that the block rates and threshold are common to the whole nation but vary from year to year. In addition, the normative amounts can be different among districts and between urban and rural classifications. It also differs between the summer and winter season. The analysis uses the only summer tariff schedules to make them consistent with the sample period.

[17] An alternative is to use the Nordin's difference variable as it is. The main estimation results have not change much even if the logarithm is not taken.

[18] The home appliance ownership is represented as the number of appliances, rather than dummy variables. Our approach is more informative because some households own multiple appliances. But the main estimation results have been found robust even if the binary variables are used instead.

Table 5. Summary statistics

	Abb.	Obs.	Mean	Std.Dev.	Min	Max
Monthly power consumption (kWh)	q	4762	355.57	207.89	0.24	4,216.11
Dummy for meter installed	I	4762	0.88	0.33	0	1
Marginal price 1/	MP	4762	7.96	1.94	4.21	9.21
Nordin's difference variable 1/	D	4762	774	655	-5,673	3,684
Monthly average high temperature	$TEMP$	4762	26.10	3.41	14.60	35.30
Monthly precipitation	$PREC$	4762	61.42	44.50	2.00	237.70
Monthly income 1/	Y	4762	38,204	52,950	100	1,627,629
Number of household members	HH	4762	4.55	1.60	1	16
Dummy for power use for lighting		4762	1.00	0.06	0	1
Dummy for power use for heating		4762	0.31	0.46	0	1
Dummy for power use for cooking		4762	0.49	0.50	0	1
Dummy for power use for water heating		4762	0.72	0.45	0	1
Dummy for power use for others		4762	0.91	0.28	0	1
Dummy for gas use for lighting		4762	0.01	0.11	0	1
Dummy for gas use for heating		4762	0.44	0.50	0	1
Dummy for gas use for cooking		4762	0.70	0.46	0	1
Dummy for gas use for others		4762	0.01	0.08	0	1
Number of home appliances owned:						
Color TV		4762	1.14	0.51	0	5
Video		4762	0.36	0.50	0	4
Refrigerator		4762	0.96	0.28	0	4
Freezer		4762	0.01	0.12	0	3
Washer		4762	0.72	0.46	0	2
Dishwasher		4762	0.02	0.14	0	2
Electric or gas stove		4762	0.80	0.44	0	6
Air conditioner		4762	0.08	0.33	0	5
Water Boiler		4762	0.63	0.51	0	3
Computer		4762	0.08	0.28	0	3
Duration of power outages per day (hours)		4762	3.59	3.29	0	22
Dummy for urban areas		4762	0.65	0.48	0	1
Memorandum items:						
Monthly electricity payment 1/		4762	2,252	1,825	1	37,000
Block rate below threshold 1/	BR_1	4762	4.44	0.15	4.21	4.61
Block rate above threshold 1/	BR_2	4762	9.01	0.25	8.42	9.21
Block tariff threshold (kWh)	q_0	4762	247.23	41.73	210	300
Normative amount of consumption (kWh)	$\overline{q}$	4678	341.69	73.69	150	400

1/ In constant 2005 Albania lek.

VI. Main Estimation Results and Policy Implications

First of all, the OLS estimation is performed (Table 6). The price elasticity is found positive. This is no doubt biased for many uncontrolled bias factors. Particularly, the positive elasticity is attributable to the typical failure to control the price endogeneity under the increasing block tariff regime. In the raw data, it is natural that larger-volume consumers are faced with higher marginal rates by construction. Therefore, the price coefficient tends to be positive without proper treatment.

Second, the marginal price and Nordin's difference variable are replaced with their predicted values based on the Hewlett's expansion of the Nordin's difference. The price elasticity is still positive and significant. As mentioned above, this approach may still fail to remove the simultaneity between price and quantity. On the other hand, the metering has a significant negative coefficient, meaning that metering matters to electricity consumption. It is interpreted as a piece of evidence that unmetered customers are systematically overconsuming electricity compared to the norms that they are facing. The similar result has been obtained when using the tariff structure as a set of instruments. The metering effect is found negative and significant; but the coefficient of the marginal rate is significantly positive.

By contrast, the Terza two-stage probit estimation shows that the price elasticity is significantly negative at –0.89. This looks to be within a reasonable range in comparison with the existing literature. However, the coefficient of metering is found negative but insignificant. Therefore, the hypothesis that the norm of consumption is not biased is rejected in most cases. The norm is likely to be underestimated. On the other hand, the price effect remains inconclusive. The partial unobservability and self-selection of metering may have to be addressed.

Table 6. OLS, 2SProbit and IV estimation with metering assumed to be exogenous

	OLS		Hewlett OLS estimator 1/		Terza two-stage probit estimator 2/		IV using tariff structure	
I	–0.163	***	–0.040	***	–0.003		–0.583	***
	(0.017)		(0.014)		(0.026)		(0.117)	
ln*MP*	0.565	***	1.023	***	–0.886	***	0.048	***
	(0.037)		(0.065)		(0.205)		(0.005)	
ln*D*	0.016	***	0.008	***	0.009	***	–0.382	***
	(0.001)		(0.002)		(0.002)		(0.032)	
ln*TEMP*	0.145	**	0.041		0.204	***	0.087	
	(0.057)		(0.054)		(0.049)		(0.062)	
ln*PREC*	–0.038	***	–0.023	***	–0.039	***	–0.022	**
	(0.009)		(0.009)		(0.008)		(0.010)	
ln*Y*	0.020	**	0.021	**	0.031	***	0.027	***
	(0.008)		(0.008)		(0.007)		(0.009)	
ln*HH*	0.057	***	0.058	***	0.086	***	0.066	***
	(0.021)		(0.021)		(0.016)		(0.022)	
D(*Power for lighting*)	0.144	**	0.152	**	0.140	*	0.120	*
	(0.059)		(0.062)		(0.076)		(0.068)	
D(*Power for heating*)	0.068	***	0.067	***	0.069	***	0.052	***
	(0.015)		(0.015)		(0.013)		(0.017)	
D(*Power for cooking*)	0.037	***	0.043	***	0.011		0.046	***
	(0.014)		(0.014)		(0.013)		(0.018)	
D(*Power for water heating*)	0.030	*	0.024		0.035	**	0.046	***
	(0.016)		(0.016)		(0.016)		(0.017)	
D(*Power for others*)	0.023		0.030		–0.004		0.032	
	(0.028)		(0.028)		(0.019)		(0.030)	
D(*Gas for lighting*)	0.016		0.032		–0.041		–0.033	
	(0.042)		(0.041)		(0.049)		(0.050)	
D(*Gas for heating*)	0.003		–0.001		0.003		–0.002	
	(0.014)		(0.014)		(0.012)		(0.015)	
D(*Gas for cooking*)	–0.037	**	–0.029	*	–0.054	***	–0.015	
	(0.017)		(0.017)		(0.014)		(0.019)	
D(*Gas for others*)	0.090		0.099		0.129	**	0.106	
	(0.097)		(0.097)		(0.063)		(0.100)	
ln*TV*	0.0064	*	0.0068	**	0.0001		0.0076	**
	(0.0033)		(0.0034)		(0.0024)		(0.0036)	
ln*Video*	0.0022	***	0.0021	**	0.0020	***	0.0025	***
	(0.0008)		(0.0008)		(0.0007)		(0.0009)	
ln*Refrigerator*	0.0043	*	0.0040	*	–0.0013		0.0051	**
	(0.0022)		(0.0022)		(0.0019)		(0.0023)	
ln*Freezer*	0.0042		0.0038		0.0030		0.0043	
	(0.0031)		(0.0030)		(0.0030)		(0.0033)	
ln*Washer*	0.0031	***	0.0027	***	0.0012		0.0042	***
	(0.0010)		(0.0010)		(0.0010)		(0.0012)	
ln*Dishwasher*	0.0111	***	0.0112	***	0.0137	***	0.0106	***
	(0.0026)		(0.0026)		(0.0023)		(0.0027)	
ln*Stove*	0.0040	***	0.0036	***	0.0029	***	0.0048	***
	(0.0010)		(0.0010)		(0.0011)		(0.0011)	
ln*AirConditioner*	0.0103	***	0.0098	***	0.0097	***	0.0119	***

	(0.0015)		(0.0016)		(0.0013)		(0.0016)	
ln*Water Boiler*	0.0001		0.0001		0.0020	**	0.0010	
	(0.0009)		(0.0009)		(0.0009)		(0.0011)	
ln*Computer*	0.0041	***	0.0044	***	0.0042	***	0.0042	***
	(0.0014)		(0.0014)		(0.0012)		(0.0015)	
ln*PowerOutages*	0.0007		0.0003		0.0016	*	0.0001	
	(0.0009)		(0.0009)		(0.0008)		(0.0009)	
D(*Urban*)	0.141	***	0.128	***	0.167	***	0.167	***
	(0.015)		(0.015)		(0.015)		(0.022)	
Constant	4.223	***	3.414	***	6.990	***	6.767	***
	(0.251)		(0.229)		(0.487)		(0.365)	
Obs.	4762		4762		4494		4678	
Adj R-squared	0.552		0.549				0.495	
F-statistics	96.78		96.33				62.31	
Wald chi2					1780.39			
λ					0.180	***		
					(0.053)			
Number of district dummies	35		35		34		35	

1/ In the Hewlett estimation model, ln*MP* and ln*D* are replaced with the predicted values in the equation that expands the Nordin's difference variable.

2/ One of the district fixed-effects is omitted because it predicts success perfectly.

Note: The dependent variable is the log of observed electricity consumption (kWh). The robust standard errors are shown in parentheses. *, ** and *** indicate the 10%, 5% and 1% significance levels, respectively.

The Nelson-Olsen estimation shows that the metering effect is significant; the coefficient is estimated at –1.477. Since the metering variable is not in logarithm, the elasticity of electricity consumption with respect to metering can be calculated as about –0.26. This confirms that the normative consumption amounts are systematically downward biased. Unmetered customers would be likely overconsuming electricity. It is consistent with theory.

The price elasticity is now also considered unbiased and found negative, though statistically insignificant.[19] Note that in this specification, the marginal prices and Nordin's difference variable are replaced with their predicted values over the instrumental variables and other exogenous covariates. This aims to focus on the issues of partial unobservability and self-selection of metering and avoid further complications in the estimation. Not surprisingly,

[19] An interactive term between the meter installation and the marginal price can be introduced to examine the price effect for metered customers. This is because the price effect may be limited when customers do not have meters. However, the coefficient of the interactive term has been found insignificant and positive. And the coefficient of ln*MP* remained negative and insignificant.

these main estimation results have been found robust if all the endogenous variables, including metering *I*, are instrumented directly by our instrumental variables (i.e., block rates, threshold and norm). Thus, it is concluded that metering is a powerful instrument to refrain from non-essential electricity use by households, while the pricing effect is inconclusive. It is negative as expected, but the statistical significance is limited.

One of the possible reasons for this is that the data do not have sufficient variation in marginal prices during the sample period. The marginal rates were increased but the variation is very small (see Table 4). Therefore, it is statistically less likely that the price variable could explain the electricity demand. Nonetheless, this does *not* mean that pricing policies are useless to manage the electricity demand, because the Nordin's difference variable almost always has a positive and significant coefficient. By construction, the Nordin's difference can be increased by lowering the first block rate, raising the second block rate or increasing the threshold between the two blocks. Therefore, the electricity demand would be reduced by raising the first block marginal rate. Similarly, the demand could be curbed by lowering the second block tariff and threshold between the blocks. All of these measures will reduce the potential benefits of low-volume customers from the increasing block tariff structure.

A policy implication is straightforward: The increasing block tariff mechanism will weaken the price incentives to use electricity wisely. In order to take advantage of the price incentives to curb the electricity demand, the privilege of the low marginal rates should be minimized. This means that low-volume consumers have to pay more. The evidence seems to be consistent with the policy argument that the tariff-based subsidies often mistarget the poor. It is generally difficult to address the equity issues by tariff-based subsidies. Conditional cash transfers may be more preferable to support the poor (e.g., Komives *et al.*, 2005; Goldstein and Estache, 2009).

Albania increased the household electricity tariff significantly after the sample period (Table 7). In 2006, the increasing block tariff structure was abolished. There was no difference in marginal rates between low- and high-volume consumers in 2006 and 2007. Notably, the second block rate was decreased. These were consistent changes with the above finding to curb the electricity demand. However, the marginal rate was raised only for large-volume consumers in 2008. This created a differential between the two block rates once again. In addition, the threshold between the two rates was also raised. Therefore, the implicit income transfers were increased. According to our estimation results, the increased Nordin's differential variable would push up the demand for electricity, not bring down.

Table 7. Electricity tariff structure in Albania

Year	1st block rate (lek/kWh)	2nd block rate (lek/kWh)	Threshold (kWh)	Normative consumption (kWh) 1/	
				Urban	Rural
Sample period:					
2002	4.0	8.0	300.0	356.9	244.4
2003	4.0	8.1	300.0	356.9	244.4
2004	4.5	8.9	220.0	363.8	237.0
2005	4.5	9.0	210.0	363.8	237.0
Beyond the sample period:					
2006	7.0	7.0	n.a.	363.8	237.0
2007	7.0	7.0	n.a.	363.8	237.0
2008	7.0	12.0	300	376.5	246.8
2009	7.0	12.0	300	376.5	246.8

1/ Average across districts for the summer period.
Source: Electricity Regulatory Entity, Albania.

Turning to the selection equation associated with metering, the Nelson-Olsen estimator shows that low-volume consumers are more likely to be equipped with meters (Table 8). This is also consistent with the theoretical prediction. There is little incentive for low-volume customers to stay unmetered. Moreover, the effects of $\overline{q}$ and q_0 on I are quite suggestive, though not statistically significant. It is indicated that the higher norm might promote meter installation. This is reasonable because the possibility of overconsuming electricity would shrink if the norm is raised. Further, the increased block tariff threshold might also help to increase metering. This is because more people would become able to take advantage of the lower marginal tariff, if the threshold is increased. But in order to benefit from this privilege, it is required to install a meter, because the norm is set above the threshold in most cases in Albania. Therefore, people would be willing to install electric meters. These are statistically insignificant, but the Nordin's difference has a significant impact on metering. Again, if the threshold increases, the Nodrin's difference increases, which would result in higher metering.

The result suggests that solely for metering purposes, one effective measure is to increase the block tariff threshold.[20]

Table 8. IV and Nelso-Olsen estimation with metering assumed to be endogenous

	IV	Nelson-Olsen estimator 1/	
Dependent variable	ln q (2nd stage)	I 2/	ln q
I	–1.024 ***		–1.477 ***
	(0.166)		(0.225)
ln q		–1.011 **	
		(0.485)	
ln $\overline{q}$		0.148	
		(0.279)	
ln q_0		0.191	
		(0.245)	
ln*MP*	–0.088		–0.123
	(0.189)		(0.268)
ln*D*	0.031 ***	0.026 *	0.029 ***
	(0.007)	(0.016)	(0.010)
ln*TEMP*	0.043	–0.006	0.045
	(0.067)	(0.095)	(0.093)
ln*PREC*	–0.020 *	–0.010	–0.014
	(0.011)	(0.015)	(0.016)
ln*Y*	0.035 ***	0.031 *	0.037 ***
	(0.010)	(0.017)	(0.014)
ln*HH*	0.040 *	0.066	0.049
	(0.024)	(0.059)	(0.031)
D(*Power for lighting*)	0.141 *	0.117	0.139
	(0.084)	(0.147)	(0.159)
D(*Power for heating*)	0.026	0.040	0.029
	(0.020)	(0.039)	(0.027)
D(*Power for cooking*)	0.016	0.047	0.025
	(0.020)	(0.053)	(0.028)
D(*Power for water heating*)	0.052 ***	0.050	0.054 *
	(0.020)	(0.033)	(0.029)
D(*Power for others*)	0.050	0.039	0.049
	(0.031)	(0.034)	(0.037)
D(*Gas for lighting*)	–0.025	–0.030	–0.029
	(0.052)	(0.086)	(0.093)
D(*Gas for heating*)	0.005	0.000	0.005
	(0.017)	(0.022)	(0.024)
D(*Gas for cooking*)	0.003	0.005	0.006
	(0.022)	(0.025)	(0.028)
D(*Gas for others*)	0.083	0.118	0.097

[20] This measure also has an adverse effect on the electricity demand management, as discussed. If the threshold is raised, the demand would increase.

	(0.113)	(0.138)	(0.127)
ln*TV*	0.0096 ***	0.0094 **	0.0106 ***
	(0.0036)	(0.0046)	(0.0036)
ln*Video*	0.0033 ***	0.0031 *	0.0035 **
	(0.0010)	(0.0018)	(0.0015)
ln*Refrigerator*	0.0049 *	0.0055	0.0056 *
	(0.0025)	(0.0038)	(0.0030)
ln*Freezer*	0.0022	0.0060	0.0047
	(0.0045)	(0.0068)	(0.0060)
ln*Washer*	0.0065 ***	0.0061 **	0.0074 ***
	(0.0015)	(0.0029)	(0.0022)
ln*Dishwasher*	0.0105 ***	0.0114	0.0113 **
	(0.0033)	(0.0069)	(0.0048)
ln*Stove*	0.0046 ***	0.0043 *	0.0048 **
	(0.0012)	(0.0024)	(0.0019)
ln*AirConditioner*	0.0120 ***	0.0119 **	0.0121 ***
	(0.0018)	(0.0060)	(0.0028)
ln*Water Boiler*	0.0002	0.0012	0.0007
	(0.0013)	(0.0024)	(0.0019)
ln*Computer*	0.0049 ***	0.0051	0.0052 **
	(0.0016)	(0.0033)	(0.0026)
ln*PowerOutages*	–0.0019 *	–0.0017	–0.0022
	(0.0011)	(0.0015)	(0.0018)
D(*Urban*)	0.203 ***	0.122 ***	0.201 ***
	(0.027)	(0.051)	(0.034)
Constant	6.303 ***	4.592 ***	6.816 ***
	(0.459)	(1.105)	(0.634)
Obs.	4678	4678	4678
Adj R-squared	0.396	0.204	
F-statistics	54.20		
Pseud R-squared			0.213
LR chi2			1888.26
σ_1^2		0.086	
σ_{12}		–0.011	
σ_2^2			0.518
Number of district dummies	35	35	35

1/ In the Nelson-Olsen estimator, ln*MP* and ln*D* are replaced with the predicted values from the 1st stage regressions of the IV estimator. The block rates are dropped due to multicollinearity.
2/ ln*MP* is dropped due to multicollinearity.
Note: The dependent variable is the log of observed electricity consumption (kWh). The standard errors are shown in parentheses. *, ** and *** indicate the 10%, 5% and 1% significance levels, respectively.

VII. DISCUSSION

One unexpected result is that weather conditions have no significant impact on the electricity demand. The weather-related variables tend to have insignificant coefficients, regardless of model and specification. A possible reason is that home appliance holdings might have already explained the difference in the power demand associated with weather conditions. As shown in Tables 6 and 8, the coefficients are small but significant and positive for most home appliances. For instance, the electricity demand elasticity associated with the number of air conditioners is estimated at 0.012 in the Nelson-Olsen estimation. Given the relatively low prevalence rate of air conditioning in Albania, a 100 percent increase may be possible in a fairly short term. Then, the electricity demand would increase by 0.1 percent.

The other reason may be that the data were collected during the summer. As indicated, this must limit variations in the demand associated with weather conditions. In addition, the quality of data may not be good, because of the absence of metering. This is exactly the question that the paper aims to address. Given a large number of observations that we have, it is not unreasonable to assume that the noise in the data could be somewhat normalized and treated as an idiosyncratic error.

Another possible reason may be that the specification is incorrect. However, the results have been found robust against the functional form. It has not changed significantly, even if different functional forms, such as non-logarithmic and Box-Cox specifications, were assumed. An interesting finding is, though, that the temperature relative to the average may be more relevant to changes in the electricity demand (Table 9). The effects of temperature and precipitation relative to the four year averages are examined. When the weather variables are included conditional on the hotter-than-usual and rainier-than-usual weather, the demand for electricity is found to increase with temperature. Although the general impact of temperature remains ambiguous, it is likely that higher-than-usual temperature would push up the electricity demand in Albania.

Table 9. Electricity demand estimation with different specifications for weather variables

	Biased OLS		IV estimator		Nelson-Olsen estimator	
I	–0.163 ***	–0.156 ***	–1.024 ***	–1.137 ***	–1.477 ***	–1.583 ***
	(0.017)	(0.017)	(0.166)	(0.219)	(0.225)	(0.300)
ln*MP*	0.565 ***	0.571 ***	–0.088 ***	–0.188	–0.123	–0.233
	(0.037)	(0.037)	(0.189)	(0.210)	(0.268)	(0.284)
ln*D*	0.016 ***	0.016 ***	0.031 ***	0.032 ***	0.029 ***	0.031 ***
	(0.001)	(0.001)	(0.007)	(0.008)	(0.010)	(0.011)
ln*TEMP*	0.145 **	0.284 ***	0.043	–0.171	0.045	–0.169
	(0.057)	(0.087)	(0.067)	(0.130)	(0.093)	(0.183)
$D(TEMP > \overline{TEMP}) * \ln TEMP$		–0.012 *		0.028 **		0.029 *
		(0.007)		(0.011)		(0.016)
ln*PREC*	–0.038 ***	–0.073 ***	–0.020 ***	–0.031 *	–0.014	–0.028
	(0.009)	(0.014)	(0.011)	(0.019)	(0.016)	(0.026)
$D(PREC > \overline{PREC}) * \ln PREC$		0.015 ***		0.011 *		0.012
		(0.005)		(0.006)		(0.008)
ln*Y*	0.020 **	0.021 **	0.035 **	0.037 ***	0.037 ***	0.039 ***
	(0.008)	(0.008)	(0.010)	(0.011)	(0.014)	(0.015)
ln*HH*	0.057 ***	0.056 ***	0.040 ***	0.038	0.049	0.047
	(0.021)	(0.021)	(0.024)	(0.025)	(0.031)	(0.032)
constant	4.223 ***	3.905 ***	6.303 ***	7.198 ***	6.816 ***	7.736 ***
	(0.251)	(0.322)	(0.459)	(0.567)	(0.634)	(0.750)
Obs.	4762	4762	4678	4678	4678	4678
Adj R-squared	0.552	0.553	0.396	0.352		
F-statistics	96.78	94.88	54.20	49.86		
Pseud R-squared					0.213	0.21
LR chi2					1888.26	1901.12

Other independent variables are omitted from the presentation: electricity and gas usage dummies for particular purposes, household ownership of 10 appliances, and district dummies.

Quantile regressions are performed to explore the presumably heterogeneous consumer behavior. However, the quantile technique cannot solve the endogeneity problem in price and quantity. Hence, the two-stage quantile regression (2SQR) estimator is used (Arias *et al*., 2001). Five quantiles are examined: .10, .25, .50 .75, and .90 (Table 10). The quantile estimation results have not differed significantly from the main results. However, it is found that large- and small-volume consumers are found to have different electricity demand functions. This can be interpreted as distributional impacts, because high-income households generally use more electricity.

Regardless of quantile, metering has been found useful to contain the demand for electricity. But the demand appears less elastic for large-volume customers. They are mostly the rich and would continue using electricity regardless of whether metered or not. Similarly, changes in the tariff structure will mainly affect small-volume consumers, who are presumably the poor. The Nordin's difference variable has a significantly positive coefficient only for the three lowest quantiles. Thus, for instance, if the threshold between the two blocks is lowered, it is the poor who would reduce the demand for electricity. The income elasticity is consistent with these findings; small-volume energy users are more likely to increase or decrease if their income changes.

With regard to the effect of home appliance holding, the use of electricity for water heating is found a major factor to add to the household demand for electricity. This is a consistent result with the previous results in Table 8. In addition, three home appliances are found particularly important in connection with the future potential growth in household income: dish washer, air conditioner and computer. For these home appliances, the coefficients are significantly positive and increase with the level of electricity consumption. This implies that the electricity demand could surge if the economy grows and more people become able to afford them, as shown in the literature (e.g., Matsukawa, 2001; Reiss and White, 2005). As income increases, more households would have the last column demand function of Table 10. Therefore, the demand could increase considerably.

Table 10. Two-stage quantile regression estimation

	Quantile				
	.10	.25	.50	.75	.90
I	–1.279 ***	–1.267 ***	–1.287 ***	–1.037 ***	–0.437 ***
	(0.227)	(0.147)	(0.104)	(0.152)	(0.169)
ln*MP*	0.080	0.059	0.237 *	0.426 **	–0.093
	(0.283)	(0.178)	(0.123)	(0.179)	(0.207)
ln*D*	0.028 ***	0.031 ***	0.025 ***	0.004	0.010
	(0.010)	(0.006)	(0.004)	(0.006)	(0.007)
ln*TEMP*	0.084	0.150 **	–0.001	0.076	0.059
	(0.098)	(0.062)	(0.043)	(0.062)	(0.069)
ln*PREC*	–0.024	–0.016 *	–0.038 ***	–0.029 ***	–0.020 *
	(0.016)	(0.010)	(0.007)	(0.011)	(0.013)
lnY	0.070 ***	0.050 ***	0.042 ***	0.039 ***	0.034 ***
	(0.014)	(0.009)	(0.006)	(0.010)	(0.011)
ln*HH*	0.088 **	0.072 ***	0.005	0.011	0.023
	(0.036)	(0.021)	(0.014)	(0.021)	(0.024)
D(Power for lighting)	0.069	0.071	0.134 *	0.157	0.151 *
	(0.132)	(0.101)	(0.071)	(0.101)	(0.094)
D(Power for heating)	0.034	0.020	0.010	0.007	0.038 *
	(0.029)	(0.018)	(0.013)	(0.018)	(0.021)
D(Power for cooking)	0.055 *	0.032 *	–0.005	–0.027	0.010
	(0.030)	(0.019)	(0.013)	(0.019)	(0.021)
D(Power for water heating)	0.050 *	0.065 ***	0.035 ***	0.045 **	0.047 **
	(0.028)	(0.019)	(0.013)	(0.019)	(0.022)
D(Power for others)	0.055	0.026	0.024	0.034	0.007
	(0.038)	(0.024)	(0.017)	(0.024)	(0.027)
D(Gas for lighting)	–0.065	–0.027	0.013	0.026	–0.041
	(0.094)	(0.060)	(0.042)	(0.062)	(0.062)
D(Gas for heating)	0.068 ***	0.022	0.019 *	0.001	–0.033
	(0.025)	(0.016)	(0.011)	(0.016)	(0.018)
D(Gas for cooking)	–0.011	–0.015	–0.019	–0.032 *	0.001 *
	(0.031)	(0.018)	(0.013)	(0.019)	(0.021)
D(Gas for others)	0.052	–0.065	0.007	0.073	0.148
	(0.131)	(0.080)	(0.057)	(0.081)	(0.096)
ln*TV*	0.0087 **	0.0074 ***	0.0051 ***	0.0031	0.0026
	(0.0037)	(0.0024)	(0.0017)	(0.0025)	(0.0026)
ln*Video*	0.0049 ***	0.0040 ***	0.0021 ***	0.0030 ***	0.0028 ***
	(0.0016)	(0.0010)	(0.0007)	(0.0010)	(0.0011)
ln*Refrigerator*	0.0023	0.0038 *	0.0019	–0.0004	0.0004
	(0.0032)	(0.0020)	(0.0014)	(0.0020)	(0.0023)
ln*Freezer*	–0.0004	–0.0082 **	0.0004	0.0043	0.0028
	(0.0059)	(0.0037)	(0.0026)	(0.0037)	(0.0038)
ln*Washer*	0.0133 ***	0.0094 ***	0.0044 ***	0.0051 ***	0.0047
	(0.0021)	(0.0014)	(0.0010)	(0.0014)	(0.0015)
ln*Dishwasher*	0.0093 *	0.0089 ***	0.0118 ***	0.0128 ***	0.0135 ***
	(0.0048)	(0.0032)	(0.0022)	(0.0031)	(0.0033)
ln*Stove*	0.0067 ***	0.0044 ***	0.0047 ***	0.0055 ***	0.0049 ***

	(0.0019)	(0.0012)	(0.0009)	(0.0013)	(0.0014)
ln*AirConditioner*	0.0080 ***	0.0094 ***	0.0128 ***	0.0131 ***	0.0116 ***
	(0.0028)	(0.0019)	(0.0013)	(0.0020)	(0.0023)
ln*Water Boiler*	0.0031	–0.0003	–0.0019 **	–0.0009	0.0010
	(0.0020)	(0.0013)	(0.0009)	(0.0013)	(0.0015)
ln*Computer*	0.0003	0.0048 ***	0.0028 **	0.0051 ***	0.0058 ***
	(0.0025)	(0.0017)	(0.0012)	(0.0018)	(0.0021)
ln*PowerOutages*	–0.0042 **	–0.0019 *	–0.0015 *	–0.0024 **	–0.0024 *
	(0.0018)	(0.0012)	(0.0008)	(0.0012)	(0.0013)
D(*Urban*)	0.229 ***	0.164 ***	0.198 ***	0.245 ***	0.228 ***
	(0.034)	(0.022)	(0.016)	(0.022)	(0.024)
Constant	5.057 ***	5.352 ***	6.040 ***	5.519 ***	6.313 ***
	(0.670)	(0.416)	(0.289)	(0.419)	(0.465)
Obs.	4678	4678	4678	4678	4678
Pseudo R-squared	0.315	0.281	0.268	0.264	0.273
Number of district dummies	35	35	35	35	35

1/ In the two-stage quantile regression, *I*, ln*MP* and ln*D* are replaced with the predicted values from the 1st stage regressions of the IV estimator.
Note: The dependent variable is the log of observed electricity consumption (kWh). The standard errors are shown in parentheses. *, ** and *** indicate the 10%, 5% and 1% significance levels, respectively.

VIII. Conclusion

The paper examined residential electricity demand in Albania, with light cast on the potential impacts of metering and climatic conditions. Given volatile international energy prices and expected global warming, it is becoming increasingly important to manage the demand for electricity or energy in general. To achieve the successful demand side management, metering is essential because it is difficult to design an efficient pricing mechanism without knowing customers are actually consuming energy.

In Albania, metering has long been an alleged concern, including malfunctioning meters, falsification of meter readings and illegal connections. The country’s electricity transmission and distribution losses have been substantial until recently. This is mostly attributable to these nontechnical inefficiencies and partly to technical losses. In addition, Albania is considered to be one of the most vulnerable countries to external energy shocks and climatic conditions, because the country is dependent more than 95 percent on hydropower for domestic electricity generation. In the future, less precipitation is expected and more droughts could happen. Therefore, it is critical to strengthen the electricity demand management and encourage people to increase energy efficiency and reduce non-essential use of electricity.

The paper found that metering is a powerful instrument to refrain from non-essential electricity use by households. Without metering, customers would likely overconsume electricity, compared to the normative amounts applied to them. Although the price elasticity is found small and statistically insignificant, it is shown that the electricity demand could be curbed by raising the first block rate, lowering the second block rate or decreasing the threshold between the two blocks. Thus, as usually indicated in the literature, tariff-based subsidies may not be compatible with the economic incentives to motivate efficient energy use. In addition, it is found that weather conditions and household ownership of home appliances affect the demand for electricity. Particularly, higher-than-usual temperature would increase the demand. Therefore, not only metering but also pricing and climatic conditions need to be taken into account to manage the electricity demand effectively.

APPENDIX. A SIMPLE MODEL FOR METERING

This appendix establishes a simple theoretical model to examine whether non-metered customers would over- or under-consume electricity. In case some of the customers are not equipped proper meters, a common practice is to apply the predetermined normative amount of consumption. The normative amount can differ depending on location, household structure and/or owned home appliances. For simplicity, however, it is assumed that the normative consumption is uniformly set at the average amount of consumption among metered customers. The consequence is simple: Overconsumption by non-metered customers would happen.

Suppose that there are in total *n* customers, $i=1,\cdots,n$, out of which *m* customers ($i=1,\cdots,m$) have meters and the rest ($i=m+1,\cdots,n$) are unmetered. Each consumer *i*'s demand for electricity (or water) is denoted by q_i^*. With maters installed, this value can be observed as the amount of billed consumption, q_i. By contrast, in the absence of meters this is unobservable and remains to be a latent value. Instead, the recorded value is a normative amount of consumption predetermined by a utility operator or regulator, $\bar{q}$. This may or may not be consistent with the actual consumption.

$$q_i = \begin{cases} q_i^* & \text{if metered} \\ \bar{q} & \text{otherwise} \end{cases} \tag{a1}$$

For simplicity, the uniform and linear pricing is considered; the unit rate is uniform for everyone and constant regardless of the amount of consumption.[21] In addition, the average pricing principle is assumed; this is considered theoretically suboptimal but frequently used because of its advantage to achieve full cost recovery, especially under the circumstances

[21] In reality, nonlinearity of the tariff structure is another complexity in utility services, which will be taken into account in the following empirical analysis.

where the average cost of production continues to decrease with output. The price is calculated by the total cost (*TC*) divided by total consumption measured (or billed):

$$p = TC \Big/ \sum_i q_i \tag{2a}$$

Note that this cannot be calculated based on the actual amount of consumption, q_i^*, because we can observe this only for metered customers. Finally, it is assumed that the normative consumption volume is set at the average consumption observed from metered customers $i = 1, \cdots, m$. This will be applied for all unmetered households:

$$\bar{q}_{(m)} = \sum_{i=1}^{m} q_i \Big/ m \tag{a3}$$

Letting I_i be the indicator function for metered customers, consider the incentive for a marginal unmetered customer, $i = m+1$. The current (monthly) payment, $c(q_i; I_i)$, for unmetered consumers is:

$$c(q_{m+1} \mid I_{m+1} = 0) = \frac{TC}{\sum_{i=1}^{m} q_i + n\bar{q}_{(m)}} \bar{q}_{(m)} \tag{a4}$$

If this consumer decides to install a meter while holding everything else constant, her payment will become:

$$c(q_{m+1} \mid I_{m+1} = 1) = \frac{TC}{\sum_{i=1}^{m} q_i + q_{m+1} + (n-m-1)\dfrac{\sum_{i=1}^{m} q_i + q_{m+1}}{m+1}} q_{m+1} + \phi \tag{a5}$$

where ϕ is a positive installation cost, which can be a one-time payment but is modeled as a part of monthly payment in Equation (a5).

When comparing Equations (a4) and (a5), it is clear that the meter installation would bring about at least three effects on her payment. First, her bill is now calculated based on the actual amount of consumption, not the normative level. This is the most apparent and direct effect. Second, although the normative level is no longer applied for this customer, it would still affect her payment because the normative amount of consumption is recalculated given the newly observed q_{m+1}, i.e., $\overline{q}_{(m)} \neq \overline{q}_{(m+1)}$.[22] Third, the average price will also be revised, because q_{m+1} is now measureable and the normative level is also adjusted.[23] Therefore, the customer's decision to move from an unmetered to metered tariff structure may not appear straightforward. For instance, if an unmetered customer is consuming less than the current norm, the meter installation would reduce her payment because of the reduced quantity by $\overline{q}_{(m)} - q_{m+1}$. At the same time, however, the applicable unit price may change and increase because her move from an unmetered to metered regime would reduce the total amount of measurable consumption by $\overline{q}_{(m)} - q_{m+1}$. The move will also raise the normative consumption amount that would be applied for the rest of the unmetered customers, whence pushing up the price.[24]

The net incentive for a marginal unmetered customer to install a meter is:

[22] If the predetermined level of normative consumption were accurate in the sense that the (m+1)th customer actually would have consumed $\overline{q}_{(m)}$, the normative level would not be changed. However, as will be shown, the normative amount would be likely downward biased. Therefore, the normative consumption level must be revised.

[23] Technically, if $q_{m+1} = \left(\frac{m(m+1)}{n} + 1 \right) \overline{q}_{(m)}$, then the average price would not change. However, this condition would not hold in our setting; the normative amount would be downward biased.

[24] In case the customer is consuming more than the norm, everything will reverse: higher consumption but lower prices.

$$\Delta c \equiv c(q_{m+1} \mid I_{m+1} = 0) - c(q_{m+1} \mid I_{m+1} = 1)$$
$$= \left(\frac{m}{n}\right)\left(\frac{TC}{\sum_i^{m+1} q_i}\right)\left(\bar{q}_{(m)} - q_{m+1}\right) - \phi \qquad \text{(a6)}$$

The equation suggests several important predictions. First, if ϕ is large, there is no incentive to install a meter. This is consistent with the government policy to subsidize meter installation especially in units with low-income tenants, as implemented in Albania and other countries.

Proposition 1. *If the cost of meter installation is significantly high, there is no incentive to install a meter.*

Equation (a6) also indicates that even if ϕ is small enough, there is no incentive for overconsuming customers to install a meter because $\bar{q}_{(m)} - q_{m+1} < 0$. In other words, only the customers who are currently underconsuming electricity or water compared with the norm would be motivated to install a new meter.

Proposition 2. *Even if the meter installation cost is small, there is no incentive to install meters if consumers are overconsuming.*

Equation (a6) has several interesting comparative static implications. Since the first term is the ratio of metered to unmetered customers, the incentive to install a new meter would be relatively strong when the majority of customers are equipped with meters. Intuitively, this is because the normative amount in effect is expected to be more accurate and would not leave much incentive for unmetered customers to keep unmetered. On the contrary, if the majority of customers do not have meters, people would be less willing to install a meter. Hence, some government's interventions might be necessary, such as installation cost subsidies, aggressive campaigns against non-metering, and mandatory installation by regulation.

Proposition 3. *In the presence of ϕ, the incentive to install a meter increases with the ratio of metered to unmetered customers. Conversely, there is a risk that no one would install meters, when the majority of customers have not installed meters.*

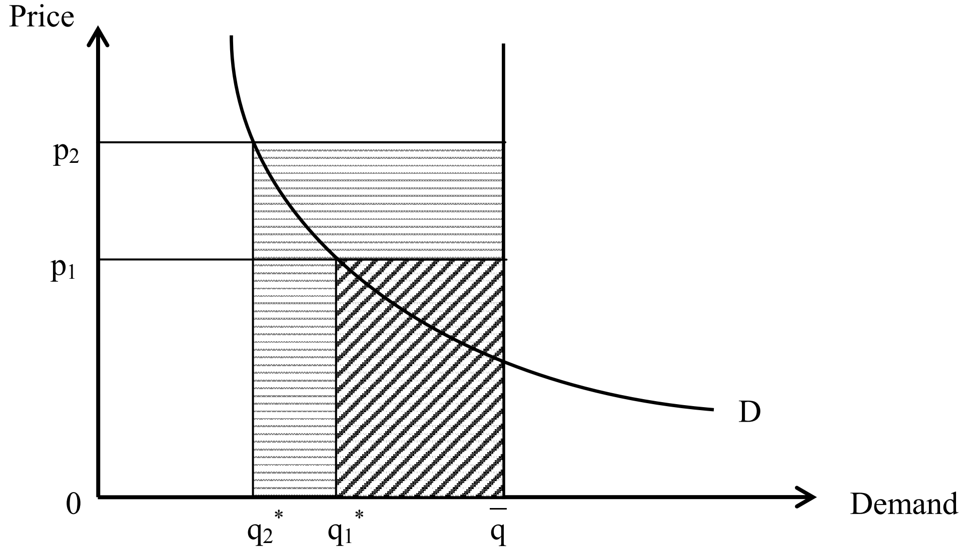
Finally, holding everything else constant, Equation (a6) means that the incentive to install a meter is a linear increasing function with the average price. Note that $TC \Big/ \sum_i^{m+1} q_i = p\left(\sum_i^{m+1} q_i \Big/ \sum_i q_i\right)^{-1}$.[25] As illustrated in Figure A1, the excess cost of not having a meter and thus being used the normative consumption level $\overline{q}$, instead of q_1 or q_2, would be much larger when price is higher ($p_2 > p_1$).

Proposition 4. *In the presence of ϕ, the incentive to install a meter would increase proportionally with the average price, which would be charged when a meter is installed.*

Although not all the propositions are necessarily testable with real data, the major theoretical consequence of incomplete metering this: Customers would endogenously decide whether to install a meter, depending on how much energy or water they intend to use. In addition, the presence or absence of meters would also affect the consumption behavior. Especially, overconsumption or underestimation of the normative consumption level would be unavoidable. It is suggested that unmetered consumers would overconsume electricity, compared to the predetermined norm.

[25] This can also be considered as the highest possible price under the average cost pricing regime under the assumption that only metered customers had to pay.

Figure A1. Excess cost of not having a meter and being applied for the normative amount of consumption
Source: Author's illustration.



REFERENCE

Amemiya, Takeshi. 1979. The estimation of a simultaneous equation tobit model. *International Economic Review*, Vol. 20, pp. 169-181.

Andrew, Clinton. 1989. Anticipating air conditioning's impact on the world's electricity producers. *Energy Journal*, Vol. 10, pp. 107-120.

Basani, Marcello, Jonathan Isham, Barry Reilly. 2008. The determinants of water connection and water consumption: Empiirical evidence from a Cambodian household survey. *World Development*, Vol. 36, pp. 953-968.

Briceno-Garmendia, Cecilia, Karlis Smits, Vivien Foster. 2008. Financing public infrastructure in Sub-Saharan Africa: Patterns and emerging issuers. Africa Infrastructure Country Diagnostic, Background Paper No. 15. The World Bank.

Davis, Lucas. 2008. Durable goods and residential demand for energy and water: evidence from a field trial. *RAND Journal of Economics*, Vol. 39, pp. 530-546.

Deller, Steven, David Chicoine, Ganapathi Ramamurthy. 1986. Instrumental variable approach to rural water service demand. *Southern Economic Journal*, Vol. 53, pp. 333-346.

Dubin, Jeffrey, Daniel McFadden. 1984. An econometric analysis of residential electric appliance holdings and consumption. *Econometrica*, Vol. 52, pp. 345-362.

ESMAP. 2009. *Climate Vulnerability Assessments: An Assessment of Climate Change Vulnerability, Risk, and Adaptation in Albania's Energy Sector*. Energy Sector Management Assistance Program.

Fernandez, Viviana. 2000. Decisions to replace consumer durables goods: An econometric application of wiener and renewal processes. *The Review of Economics and Statistics*, Vol. 82, pp. 452-461.

Filippini, Massimo, Shanali Pachauri. 2004. Elasticities of electricity demand in urban Indian households. *Energy Policy*, Vol. 32, pp. 429-436.

Frondel, Manuel, Jorg Peters, Colin Vance. 2008. Identifying the rebound: Evidence from a German household panel. *The Energy Journal*, Vol. 29, pp. 145-163.

Goldstein, Markus, Antonio Estache. 2009. The scope and limits of subsidies, in *Stuck in the Middle: Is Fiscal Policy Failing the Middle Class?* eds. by Antonio Estache and Danny Leipziger, pp. 75-96. The Brookings Institution.

Hausman, Jerry, David Wise. 1976. The evaluation of results from truncated samples: The New Jersey income maintenance experiment. *Annals of Economic and Social Measurement*, Vol. 5, pp. 421-445.

Hausman, J.A., M. Kinnucan, D. McFadden. 1979. A two-level electricity demand model: Evaluation of the Connecticut time-of-day pricing test. *Journal of Econometrics*, Vol. 10, pp. 263-289.

Hewlett, James. 1977. Changing patterns of household's consumption of energy commodities. *Preceedings of the American Statistical Association Business and Economic Section*, Part I, pp. 99-108.

Komives, Kristin, Jonathan Halpern, Vivien Foster, Quentin Wodon. 2005. *Water, Electricity, and the Poor: Who Benefits from Utility Subsidies?* The World Bank.

Komives, Kristin, Jonathan Halpern, Vivien Foster, Quentin Wodon. 2006. The distributional incidence of residential water and electricity subsidies. Policy Research Working Paper No. 3878. The World Bank.

Lam, Joseph, Danny Li, S.O. Cheung. 2003. An analysis of electricity end-use in air-conditioned office buildings in Hong Kong. *Building and Environment*, Vol. 38, pp. 493-498.

Lampietti, Julian, Sudeshna Ghosh Banerjee, Amelia Branczik. 2007. *People and Power: Electricity Sector Reforms and the Poor in Europe and Central Asia*. The World Bank: Washington.

Maddala, G.S. 1983. *Limited-dependent and Qualitative Variables in Econometrics*. Cambridge University Press.

Matsukawa, Isamu, Nariyasu Ito. 1998. Household ownership of electric room air conditioners. *Energy Economics*, Vol. 20, pp. 375-387.

Matsukawa, Isam. 2001. Household response to optional peak-load pricing of electricity. *Journal of Regulatory Economics*, Vol. 20, pp. 249-267.

Nauges, Celine, Caroline van den Berg. 2009. Demand for piped and non-piped water supply services: Evidence from Southwest Sri Lanka. *Environmental and Resource Economics*, Vol. 42, pp. 535-549.

Nieswiadomy, Michael, David Molina. 1989. Comparing residential water demand estimates under decreasing and increasing block rates using household data. *Land Economics*, Vol. 65, pp. 280-289.

Pedro Antmann. 2009. Reducing technical and non-technical losses in the power sector. Background paper for the World Bank Group Energy Strategy. Washington DC: The World Bank.

Reiss, Peter, Matthew White. 2005. Household electricity demand, revisited. *Review of Economic Studies*, Vol. 72, pp. 853-883.

Small, Kenneth, Kurt Van Dender. 2007. Fuel efficiency and motor vehicle travel: The declining rebound effect. *The Energy Journal*, Vol. 28, pp. 25-51.

Terza, Joseph, W.P. Welch. 1982. Estimating demand under block rates: Electricity and water. *Land Economics*, Vol. 58, pp. 181-188.

Terza, Joseph. Determinants of household electricity demand: A two-stage probit approach. *Southern Economic Journal*, Vol. 52, pp. 1131-1139.

World Bank. 2006. Infrastructure in Europe and Central Asia Region: Approaches to sustainable services. Infrastructure Department, Europe and Central Asia Region, The World Bank.

World Bank, 2008. *Deterring Corruption and Improving Governance in the Urban Water Supply and Sanitation Sector*. Water Working Notes No. 18, The World Bank.

World Bank, 2009a. *Deterring Corruption and Improving Governance in the Electricity Sector*. The World Bank.

Yoo, Seung-Hoon. 2007. Estimation of household tap water demand function with correction for sample selection bias. *Applied Economics Letters*, Vol. 14, pp. 1079-1082.